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A Model for Predicting Flood Using Machine Learning Techniques: A Case of Adamawa State, Nigeria

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Abstracts: In recent years, Adamawa State was badly affected by the 2022 flood due to heavy rainfall, climate change and the release of water from Lagdo Dam from neighbouring Cameroon. The 2022 flood is the worst affected flood in Nigeria's history since 2012. This paper developed a model for predicting floods in Adamawa State North-East Nigeria using Artificial Neural Network. The study collected secondary data for the model. A total of 360 data samples spanning over twenty-eight (28) years comprising atmospheric and hydrological data were collected. The interval of data collected was between the years 1992 to 2021. The data collected consisted of six (8) initial columns. The data sample contains relevant parameters such as the year/month of the data, monthly mean of the max temperature, mean of the monthly minimum temperature, relative humidity, the volume of rainfall, gauge height and the class of the data. . The collected data were pre-processed, cleaned, and modelled using Jupyter Notebook, a Python Anaconda development platform for Artificial Neural to build the predictive model. The model was evaluated using a confusion matrix. The prediction accuracy was 96.37% was obtained. The study concluded that Flood predictive model will alert individuals residing in the flooded area and recent authorities so that proper measures will be taken to curtail the problem of flooding in Adamawa State, Nigeria.

1. Introduction

The damages caused by flooding in Adamawa state in recent years cannot be over emphasize as it is one of the major disasters ever reported and has caused severe personal injuries and in addition damages property and in some cases lead to loss of lives. Escalation in flooding events is indeed a dilemma through recent years, as innumerable causalities are caused by them every year (El-magd et al., 2021) Moreover, climatic change has many consequences as surge in frequency of rainfalls potentially enhance the rate of flooding. Flooding is a disaster that occurs naturally is said to be disaster as a phenomenon which is a part of earth's bio- physical processes, which can be devastating due to anthropogenic activities and climatologically factors (Adetoro and Akanni, 2018). Sella et al (2022) described floods as a major natural threat to populations worldwide causing thousands of fatalities and resulting in large economic damages annually. There are many factors that are responsible for flooding, MecGraw-Hill (2017) pointed out that a flood event may occur due to large stream flow magnitudes such that the flow rate exceeds the capacity of the main channel at a location (i.e., the flow exceeds the bank full discharge) or may occur for lower stream flow rate when the flow happens. While on the other hand Blöschl et al. (2019) attributed Population growth, urbanization, and the changing climate as contributing factors that have led to an increase in the numbers of floods in recent decades.

In most developing countries, flood hazard is a primary weather-related disaster because most developing countries do not have proper flood mitigation measures and floodplains are often heavily populated since there is no alternative place for citizens to settled down (Alfieri et al., 2018). In recent year, Nigerian has experienced heavy flood as a results unusual heavy rains and climate change as well as the released of water from the Lagdo Damo in neighboring Cameroon which began on 13 September, 2022(Wahab, 2022). The 2022 Nigeria floods have affected most of the country, displacing over 1.4 million people, killing over 600 and injuring more than 2,400, over 200,000 homes completely or partially destroyed, 110, 000 hectares of farmland destroyed, while Nigeria typically experiences seasonal flooding, the flood were the worst in the country since (Maclean, 2022).

Early detection of natural disasters such as floods can greatly assist humans in reducing the extent of the damage caused by such events. Flood events resulted in major damages amounting to millions of dollars (Brown et al., 2017). Although flood risks cannot be completely eliminated, real time flood predictive models, as an important and integral part of a flood warning service, can help to provide timely flood warnings with an adequate lead time for the public to minimize flood damages. Rainfall readings are valuable to local emergency situations, assessing flood conditions and taking appropriate actions. Advanced warning provided by early detection is critical to saving lives in flood prone areas. Advanced mathematical modeling can bring about enough difference in time. Machine learning approach is one of the popular areas in Data mining used for predicting events. Machine learning is the process through which a machine or model is provided access to data and is able to learn on its own through the data provided. Machine Learning (ML) refers to the programming of computers to enhance a performance standard through example data or experience (Kucak et al., 2018). When a machine learning algorithm is implemented, it indicates that a model is implemented that outputs appropriate information, considering that input data has been given.

Artificial Neural Network (ANN) is another extensively used method in the field of Data Mining (Coacho and Silveira, 2017).

This study is focused on developing a model using Artificial Neural Network (ANN) that will be used in predicting flood in Adamawa State North-East Nigeria. The study will in curtailing the recent disaster caused by flood in Nigeria.

2. Literature Review

Different studies have reported using various approaches towards predicting floods. Few among them have been reviewed:

Mohammed et al. (2018) investigated the use of different types of Machine Learning algorithms used in predicting flood's severity; the study also classified floods into three classes, namely: normal, high-risk and abnormal floods. The outcome of the study produced enhanced results for pre- processing of flood dataset based on time series. The study makes use of Random Forest Classifier (RFC), Support Vector Deeps (SVM), Levenberg-Marquartdt training algorithm (LEVNN), Linear Neural Network (LNN) to compare the accuracy of prediction. The results of the study revealed that RFC performed better using the performance measures examined.

Sara et al. (2019) focus on the use of Artificial Intelligence on the big data. Their research collected historical data to train the algorithm about past events and also extracted information and patterns, and understanding flood's behavior to improve the degree of preparedness and prevent damage in the events of disaster. Random Forest technique is being used as it guarantees the highest rate of accuracyforclassification.J48 decision tree and Artificial Neural Networks (ANN) are next in line for predicting flash flood and Lazy methods. Disaster monitoring methods used in the paper are based on detection algorithm based on change, where the area affected can be recognized using a complex study on pre disaster and post disaster event data.

Ren et al. (2019) conducted a study using multiple linear regression, ANN, SVM and RF to develop a flood forecasting for Yarlung Zangbo River Basin, located in China. Their study revealed that the RF model produced the highest efficiency for downscaling the temperature for Representative Concentration Pathways (RCPs) of 2.6 and 8.5 for the period 2016–2050. Ahmed et al. (2020) applied ANN, KNN, relevance vector machine (RVM) and SVM to design multi-model ensembles for precipitation, maximum and minimum temperatures, the study make used of Pakistan as the study area using 36 global climate models (GCMs), the results of the shows that RVM and KNN performed better than others. El-Haddad et al. (2021) applied four Machine Learning models to design and develop flood susceptibility maps for the WadiQena Basin, in Egypt. The results the models revealed that XGBoost came out to be the best over KNN with an AUC score of 0.902, for the flash flood prediction in after models was evaluated using receiver operating characteristics (ROC) and the AUC.

Amitkumar et al. (2018) conducted a study and developed a model for a reliable flood predicting system where the reliability is based on the ability of the system to provide advance warning. The model is developed based on the scale, types of flood, flooding behavior, types of landscape. The various approaches used are statistical, ANN and clustering approaches. This paper helps us understand the working of application software for the deployment of a disaster prediction, warning system and post disaster report.

3. Method and Materials

3.1 Study Area

The study was conducted in Adamawa State North-East Nigeria. The state is located in the north-east sub-region of Nigeria, at latitude 9.330N and longitude 12.50E with its capital in Yola. The state was created in 1991 from the defunct Gongola State and has since been one of the 36 states that presently constitute the Federal Republic of Nigeria. Adamawa State is one of the largest states in terms of land mass, occupying about 36,917km2.The state shares boundaries with Borno to the north, Gombe to the west, Taraba to the south, and Cameroon republic to the east. The State has a population of 3,106,585 (2005 estimate).

3.2 Research Instruments

The set of instruments used for this study include historical dataset for 28 years will be collected from NIMET on weather.

3.3 Data Set

For this study, raw data was collected from the upper River Benue commission located in Yola, Adamawa state. A total of 360 data samples that span over twenty eight (28) years comprising of atmospheric and hydrological data were collected. The interval of data collected was between the year 1992 to 2021. The data collected consisted of six (8) initial columns. The data sample as shown below contain relevant parameters such as year/month of the data, monthly mean of the max temperature, mean of the monthly minimum temperature, relative humidity, volume of rainfall, gauge height and the class of the data.

1	YearMonth	Monthly Mean of Max Temp	Mean monthly Min Temp	Relative Humidity (RH)	Rainfall (R)	Water Level (WL)	GAUGE HEIGHT	Class
2	1992-Jan	34.5	18.8	27	0	1.51	152.68	Normal
3	1992-Feb	37.5	20.8	21	0	1.51	152.68	Normal
4	1992-Mar	40.1	24.9	25	0	151	152.77	Normal
5	1992-Apr	39.7	27.2	47	45.1	1.54	152.71	Normal
6	1992-May	37	26.4	61	113.3	1.59	152.76	Normal
7	1992-Jun	32.8	24	76	142.4	1.79	152.96	Normal
8	1992-Jul	31.2	23.4	79	185.5	2.76	153.93	Normal
9	1992-Aug	30.5	23	84	164	4.58	155.75	Flood
10	1992-Sep	30	22.8	85	353.9	5.53	156.7	Flood
11	1992-Oct	33.6	22.5	74	97.3	4.62	155.79	Flood
12	1992-Nov	36.1	12.2	52	0	2.19	153.36	Normal
13	1992-Dec	33.5	17.7	38	0	1.77	152.94	Normal
14	1993-Jan	31.4	15.6	28	0	1.53	152.7	Normal
15	1993-Feb	33.9	18.2	23	0	1.38	152.55	Normal
16	1993-Mar	40	21.7	27	0	1.53	152.7	Normal
17	1993-Apr	40.1	25.5	42	20.8	1.46	152.63	Normal
18	1993-May	35.1	24.4	67	137.3	1.53	152.7	Normal
19	1993-Jun	33.3	23.4	80	62.9	1.77	152.94	Normal
20	1993-Jul	31	22.5	80	235.8	2.66	153.83	Normal

	YearMonth	Monthly Mean of Max Temp	Mean monthly Min Temp	Relative Humidity (RH)	Rainfall (R)	Water Level (WL)	GAUGE HEIGHT	Class
342	2020-May	41.4	26.2	60	0	3.29	154.46	Flood
343	2020-Jun	40.5	27	73	56.4	4.2	155.37	Flood
344	2020-Jul	35	26.3	83	104	5.24	156.41	Flood
345	2020-Aug	33.5	24	83	142.4	3.66	154.83	Flood
346	2020-Sep	31.1	22.8	81	167	2.07	153.24	Normal
347	2020-Oct	31.3	22.3	76	189.5	1.73	152.9	Normal
348	2020-Nov	34.5	22.4	49	58.1	1.52	152.69	Normal
349	2020-Dec	36.5	22.5	33	0	1.39	152.56	Normal
350	2021-Jan	35	18.3	34	0	1.46	152.63	Normal
351	2021-Feb	36.2	16.4	20	0	1.49	152.66	Normal
352	2021-Mar	39	18.8	35	0	1.68	152.85	Normal
353	2021-Apr	41.9	20.8	25	0	2.48	153.65	Normal
354	2021-May	40.2	24.9	45	17.1	3.45	154.62	Flood
355	2021-Jun	37.9	26.7	69	45.1	4.33	155.5	Flood
356	2021-Jul	34.7	26.4	75	113.3	4.54	155.71	Flood
357	2021-Aug	31.5	25.1	83	142.4	3.31	154.48	Flood
358	2021-Sep	30.8	24.3	81	185.6	1.94	153.11	Normal
359	2021-Oct	31.5	23.6	76	164	1.64	152.81	Normal
360	2021-Nov	34.1	23.2	49	63.1	1.47	152.64	Normal

Table 1: Showing the Sample of atmospheric and hydrological Data Collected

4 Data Pre-Processing

This data was made up of both string and numeric variables which cannot be directly modelled by the artificial neural network, therefore there are further pre-processed and reduced into a form in a way to make it more amenable for the algorithm to make predictive insights from the data. Especially, the month/year of the data collected will not contribute any useful insights into the model; hence the month/year column was removed in the main data before inputting into the artificial neural network model.

The dataset was coded into the Microsoft excel sheet and converted into a comma separated values (csv) file. This was done in order to make it easy for python data frame to read it from the jupyter notebook file folder already installed from the anaconda packages. The datasets which was eight (8) columns initially was later reduced to 7 columns to ensure that relevant parameters are used in the flood predictive model.

The final data items used in predicting flood are as shown in the table below. The independent variables for the flood prediction are: monthly mean of the max temperature, mean of the monthly minimum temperature, relative humidity, volume of rainfall, and the gauge height. While the class of the data culled from the gauge height was the dependent variable or the target class or the ground truth of the prediction. The class of the prediction was to estimate or predict whether there was flood or normal given the predictors or parameters.

In [1]:
```
import pandas as pd
dataframe = pd.read_csv("floodata.csv")
#dataframe[dataframe.Class=='flood']
dataframe
```

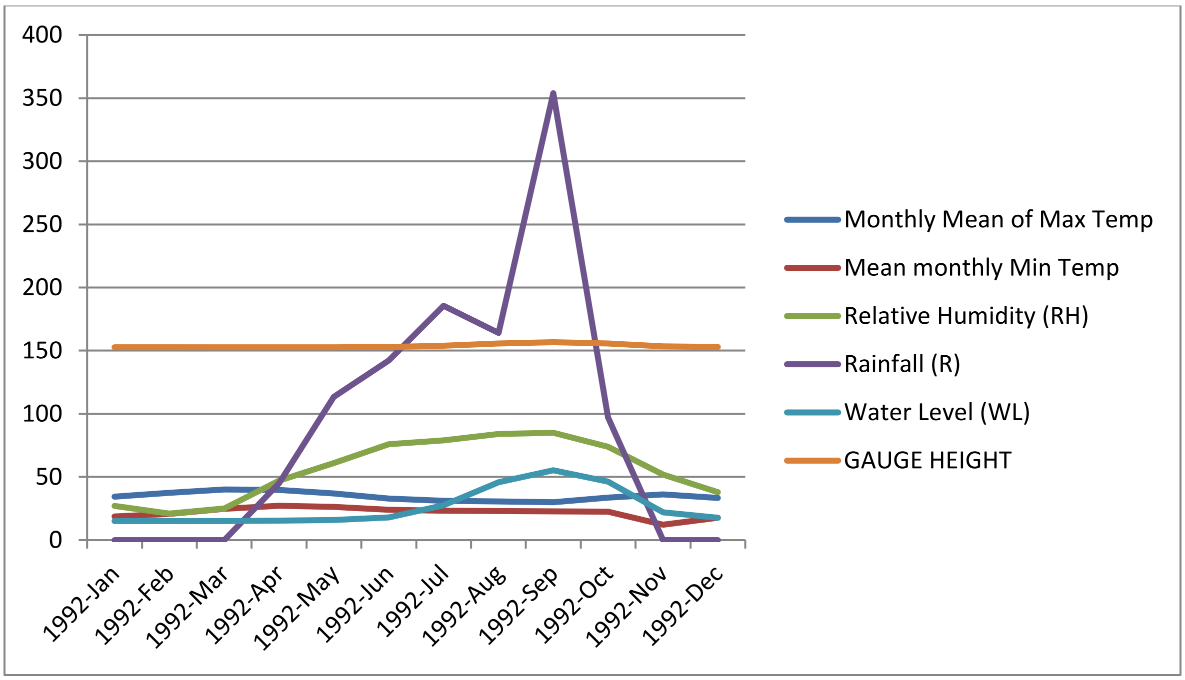
Out[1]:

	Monthly Mean of Max Temp	Mean monthly Min Temp	Relative Humidity (RH)	Rainfall (R)	Water Level (WL)	GAUGE HEIGHT (151.166 m)	Class
0	34.5	18.8	27	0.0	1.51	152.676	normal
1	37.5	20.8	21	0.0	1.51	152.676	normal
2	40.1	24.9	25	0.0	1.60	152.766	normal
3	39.7	27.2	47	45.1	1.54	152.706	normal
4	37.0	26.4	61	113.3	1.59	152.756	normal
5	32.8	24.0	76	142.4	1.79	152.956	normal
6	31.2	23.4	79	185.5	2.76	153.926	normal
7	30.5	23.0	84	164.0	4.58	155.746	flood
8	30.0	22.8	85	353.9	5.53	156.696	flood
9	33.6	22.5	74	97.3	4.62	155.786	flood

Figure 2: Showing the data sample mapped into the ANN Model

5. Data exploration and Visualization

In this study the data samples consist of 360 numbers of observations over twenty eight (28) years. It is important to see how the data realigns with the realities of the phenomenon to be modelled. The figure 3 below shows the one year graphical representation of the Flood data samples. It shows the monthly representation of the data samples such as monthly mean of the max temperature, mean of the monthly minimum temperature, relative humidity, volume of rainfall, and the gauge height.



5. ANN Model building experiment data

Artificial Neural Network model building is stochastic or probabilistic. Therefore, the model building process goes through a series of experiments, in order to ascertain the optimal number of layers and neurons at which the algorithm performs at its highest. The neural network library known as Keras is used with its Sequential stacks of layers inbuilt in python programming language that supports multi-layer network. After the dataset was partitioned and initial parameters set, the model was trained at 50 epochs in order to obtain the performance of the model and accuracy metrics as shown below:

```
Epoch 1/50
360/360 [==============================] - 0s - loss: 0.6289 - acc: 0.7611
Epoch 2/50
360/360 [==============================] - 0s - loss: 0.4762 - acc: 0.8694
Epoch 3/50
360/360 [==============================] - 0s - loss: 0.3517 - acc: 0.8944
Epoch 4/50
360/360 [==============================] - 0s - loss: 0.2721 - acc: 0.8972
Epoch 5/50
360/360 [==============================] - 0s - loss: 0.2192 - acc: 0.9167
Epoch 6/50
360/360 [==============================] - 0s - loss: 0.1845 - acc: 0.9472
Epoch 7/50
360/360 [==============================] - 0s - loss: 0.1548 - acc: 0.9528
Epoch 8/50
360/360 [==============================] - 0s - loss: 0.1350 - acc: 0.9528
Epoch 9/50
360/360 [==============================] - 0s - loss: 0.1105 - acc: 0.9722
Epoch 10/50
```

```
360/360 [==============================] - 0s - loss: 0.0291 - acc: 0.9833
Epoch 43/50
360/360 [==============================] - 0s - loss: 0.0274 - acc: 0.9889
Epoch 44/50
360/360 [==============================] - 0s - loss: 0.0296 - acc: 0.9833
Epoch 45/50
360/360 [==============================] - 0s - loss: 0.0254 - acc: 0.9861
Epoch 46/50
360/360 [==============================] - 0s - loss: 0.0287 - acc: 0.9861
Epoch 47/50
360/360 [==============================] - 0s - loss: 0.0240 - acc: 0.9972
Epoch 48/50
360/360 [==============================] - 0s - loss: 0.0242 - acc: 0.9889
Epoch 49/50
360/360 [==============================] - 0s - loss: 0.0298 - acc: 0.9861
Epoch 50/50
360/360 [==============================] - 0s - loss: 0.0243 - acc: 0.9889

: <keras.callbacks.History at 0xe07f1b0>
```

Figure 4: Showing Performance of the Model loss and accuracy Metrics

From the neural network model training loss and accuracy shown above, the metrics showed that while loss decreases, the accuracy increases with the increase in epochs as visualized below:

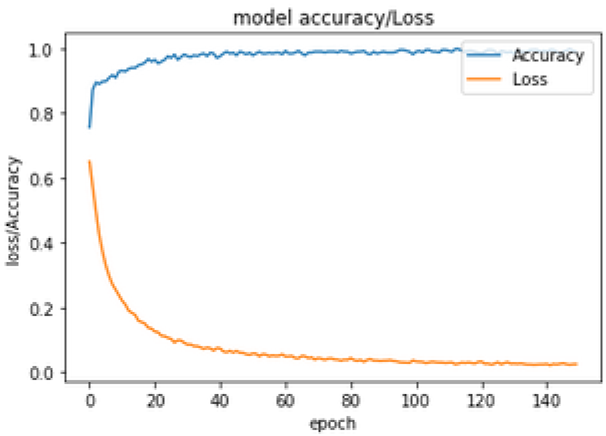


Table 1: Showing the ANN Experiment data

Layer (s)	**Neurons**	**Input layer activation function**	**Output layer activation function**	**optimizer**	**Accuracy**
1	5	Relu	Softmax	Adam	76.11%
1	10	Relu	Softmax	Adam	88.33%
1	15	Relu	Softmax	Adam	89.44%
1	20	Relu	Softmax	adam	89.72%
1	25	Relu	Softmax	adam	90.83%
1	30	Relu	Softmax	adam	91.67%
2	30, 10	Relu	Softmax	adam	95.28%
2	30, 15	Relu	Softmax	adam	95.83%
2	**30, 20**	**Relu**	**softmax**	**adam**	**96.39%**
2	30, 25	Relu	Softmax	Adam	96.39%
2	30, 25	Relu	Softmax	Adam	96.11%
2	30, 30	Relu	Softmax	Adam	96.24%

Figure 5: Model loss and accuracy visualization

From table above, the performance of the neural network reached optimum performance at an accuracy of 96.39%.

The accuracy was confirmed using confusion matrix. The confusion matrix was obtained on the test dataset in order to evaluate the model performance on unseen dataset as shown below.

	precision	recall	f1-score	support
class 0(Flood)	0.93	0.78	0.85	36
class 1(Normal/No_Flood)	0.90	0.97	0.93	72
avg / total	0.91	0.91	0.91	108

```
Confusion_Matrix Report
[[28  8]
 [ 2 70]]
```

Table: Showing the confusion matrix accuracy measurement on test dataset

From the table above, the precision, recall, f1-score of the model on test dataset was 91%.

Moreover, 28 out of 36 flood classed variables were predicted correctly, while 70 out 72 normal or no flood variables were predicted correctly

From the Keras sequential model, the final model is as shown in figure 8 below:

Layer (type)	Output Shape	Param #
dense_331 (Dense)	(None, 30)	210
dropout_216 (Dropout)	(None, 30)	0
dense_332 (Dense)	(None, 25)	775
activation_1 (Activation)	(None, 25)	0
dropout_217 (Dropout)	(None, 25)	0
dense_333 (Dense)	(None, 2)	52
activation_2 (Activation)	(None, 2)	0

Total params: 1,037.0
Trainable params: 1,037.0
Non-trainable params: 0.0

Figure 6: Showing the Keras summary of final model for Flood Prediction

6. Artificial Neural Network Model Architecture

From the ANN experiment, the final model for the flood prediction is as shown below. It has an Input layer with 6 variables, two middle layers comprising of 30 and 20 neurons each and output layer with two labels.

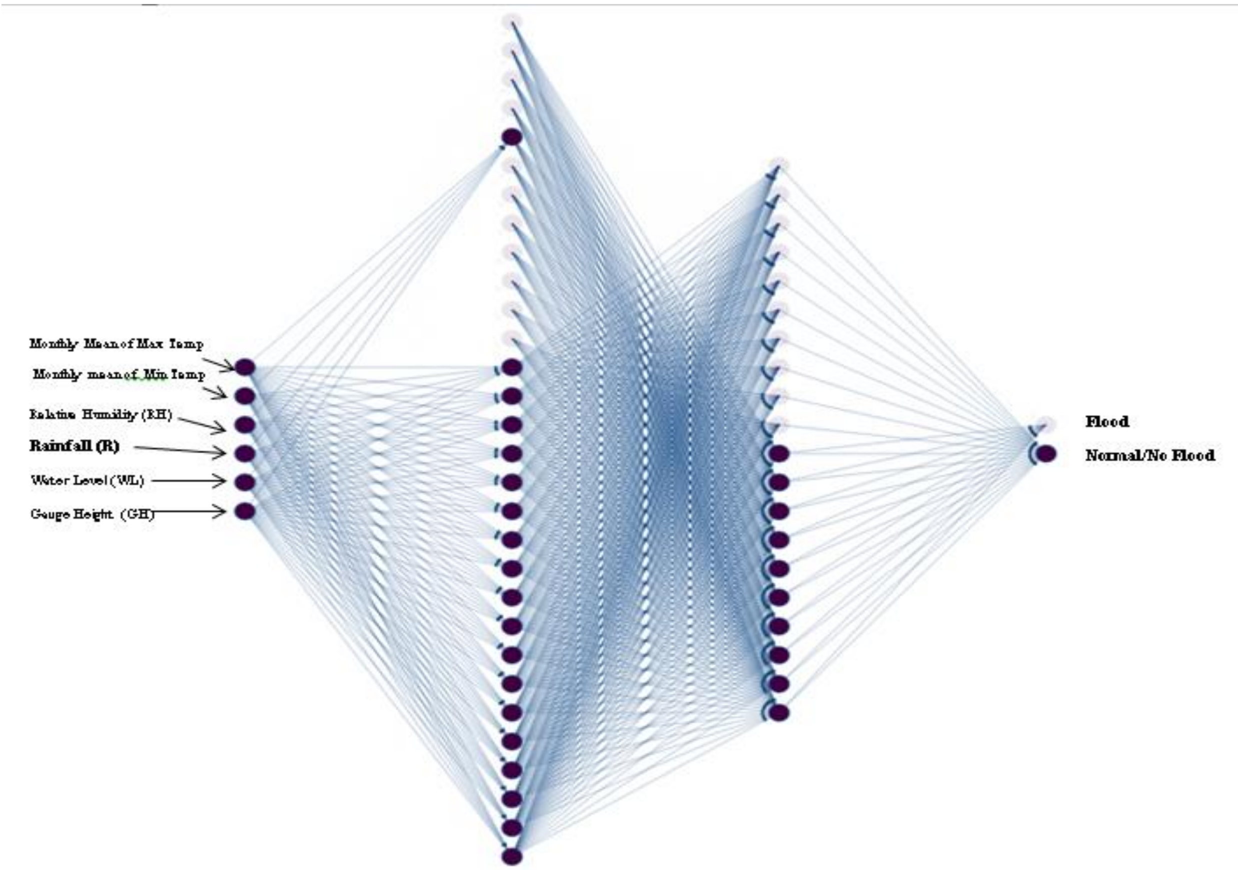


Figure 7: ANN Model architecture for Flood Prediction

7. ANN Model flood prediction

The flood prediction based on the atmospheric and hydrological dataset using the artificial neural network model was binary classification model that generates two output/labels based on the learning of the model through earlier training on input datasets. The two expected output samples from this study are:

i. Flood
ii. No flood

To make predictions, this work used the model designed to generate predictions on new data or the unseen dataset called the test dataset by calling the predict function such as predict() on the model. Below are the predicted classes:

```
========== ........................ ======
========== Encoded Prediction Codes ======
[1 1 1 0 0 1 1 1 1 1 1 1 1 1 0 1 0 0 1 0 1 0 1 0 1 1 1 1 0 0 1 1 1 1 1 0 1
 1 1 1 1 1 1 1 0 1 1 1 0 0 1 0 1 1 1 1 1 0 1 1 1 0 0 1 1 1 0 1 1 1 1 1 0 1
 0 1 0 1 0 1 1 1 1 1 0 1 1 0 0 0 0 1 1 0 1 1 1 1 1 1 1 1 1 1 1 0 1 1]
===== Corresponding Meaning of Codes======
['Normal' 'Normal' 'Normal' 'Flood' 'Flood' 'Normal' 'Normal' 'Normal'
 'Normal' 'Normal' 'Normal' 'Normal' 'Normal' 'Normal' 'Flood' 'Normal'
 'Flood' 'Flood' 'Normal' 'Flood' 'Normal' 'Flood' 'Normal' 'Flood'
 'Normal' 'Normal' 'Normal' 'Normal' 'Flood' 'Flood' 'Normal' 'Normal'
 'Normal' 'Normal' 'Normal' 'Flood' 'Normal' 'Normal' 'Normal' 'Normal'
 'Normal' 'Normal' 'Normal' 'Normal' 'Flood' 'Normal' 'Normal' 'Normal'
 'Flood' 'Flood' 'Normal' 'Flood' 'Normal' 'Normal' 'Normal' 'Normal'
 'Normal' 'Flood' 'Normal' 'Normal' 'Normal' 'Flood' 'Flood' 'Normal'
 'Normal' 'Normal' 'Flood' 'Normal' 'Normal' 'Normal' 'Normal' 'Normal'
 'Flood' 'Normal' 'Flood' 'Normal' 'Flood' 'Normal' 'Flood' 'Normal'
 'Normal' 'Normal' 'Normal' 'Normal' 'Flood' 'Normal' 'Normal' 'Flood'
 'Flood' 'Flood' 'Flood' 'Normal' 'Normal' 'Flood' 'Normal' 'Normal'
 'Normal' 'Normal' 'Normal' 'Normal' 'Normal' 'Normal' 'Normal' 'Normal'
 'Normal' 'Flood' 'Normal' 'Normal']
```

Figure: showing the prediction in binary and the encoded meaning of the flood

8. Discussion

This study has experimented and modelled the flood dataset gathered over twenty eight (28) years comprising of atmospheric and hydrological data. The interval of data collected was between the year 1992 to 2021. The dataset was modelled using the artificial neural network algorithm in order to preempt in advance the likely occurrences of flood in the future. From the research, the results showed that the artificial neural network had an optimal performance of 96.39% when the neural network was configured at 30 and 20 neurons of the middle layers. At this performance, the experimental set up was designed in such a way that issues such as overfitting and under-fitting was handled by using parameters such as drop out for neural network. Moreover, the dataset was scaled or normalized between 0 and 1 to reduce and equate the highly dimensional data. The data normalization was done using the MinMax scaler.

More so, the confusion matrix was used to reveal what actual numbers of the classes were predicted correctly.From the confusion matrix performance, the precision, recall, f1-score of the model on test dataset was 91%. Moreover, 28 out of 36 flood classed variables were predicted correctly, while 70 out 72 normal or no flood variables were predicted correctly. This showed that the "No Flood' performed better than the 'Flood' classes. This was basically on the fact that it was an imbalanced classification. The flood class was flood 116, while the No Flood class was 244. The accuracy prediction evaluation was guided by the test datasets and on the unseen dataset.

Conclusions

The devastating effects of flood on the social economic development of any country cannot be over emphasizing. Millions of farmlands are lost to flooding, millions of people are displaced from their houses and properties destroyed. This study used Artificial Neural Network and developed a model for predicting flood in Adamawa State North-East Nigeria. A total of 360 data samples that span over twenty eight (28) years comprising of atmospheric and hydrological data were collected. The interval of data collected was between the year 1992 to 2021 was used in developing the predictive model on flood. The performance of the neural network reached optimum performance at an accuracy of 96.39%. The model was evaluated using confusion matrix. To make prediction an encoded code of 0,1 which represent Norma and flood on the predicted classes was drawn from the model. Developing a model for predicting flood can save lives and reduces risk and damages of flooding. Flood predictive model provides accurate and effective early warnings in flood prone areas in Adamawa State North-East Nigeria. The implementation of this model will alert individuals residing in the flooded area and recent authorities so that proper measure will be taken to avert the effects of floods.

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